

Title of Invention: Patient Monitoring System

Technical Field

The present invention relates to a system and method for monitoring of a patient with the
5 aid of artificial intelligence.

Background

Patients cared for at home are generally elderly, immobile and highly dependent on care
provided by the family or other caregivers. In the current context of home care, monitoring
10 and measurement of a patient's clinical status is commonly performed by family and
caregivers. Basic vital signs such as blood pressure, heart rate and temperature are
obtained through appropriate medical devices, and patient symptoms or behaviour is
reported through the family or caregiver's observations.

15 During a clinician's review of the patient, the clinician relies on the information and vital
signs measurements provided by the patient's family or caregiver. Once the clinician leaves
the patient's home there is no way of directly and continuously monitoring the patient, or to
respond to the patient if a situation arises.

20 The accuracy of such measurements is limited by factors such as the correct use of
available medical equipment and human error when recording or reporting the
measurements. Additionally, the frequency of measurements is dependent on the
availability of the caregiver. This may result in a gap in monitoring at times when the
caregivers are resting or away from the patient. Furthermore, reporting of such
25 measurements and symptoms may be liable to errors during the communication process.

Current clinical management protocols rely on sporadic (spot) patient measurement, rather
than continuous data. The volume of data generated through novel continuous monitoring
devices necessitates new ways of interpreting and translating the data into clinical care
30 protocols.

Summary

In a first aspect of the invention, there is provided a computer-implemented method of
monitoring a person's health condition, the method comprising receiving sensor data of a
35 person in a bed; generating a vital signs dataset from the sensor data; and displaying the
vital signs dataset.

Preferably, the method further comprises comparing the vital signs dataset against one or more threshold values, wherein the one or more threshold values comprises predicted values from a first prediction model trained on an existing vital signs dataset and a physiological range of the vital signs; and generating an alert when the one or more threshold values are crossed. Thus, the threshold values may be made up of the predicted values and physiological feasible values. The physiological range may be predetermined and varied depending on the person being monitored. The vital signs of a person refer to a physiological signal of the person measured by the sensor, for example the measured signal strength of the sensor, heart rate, heart rate variability, respiratory rate, temperature, blood pressure, and oxygen saturation.

Preferably, the method further comprises recording an anomaly in the vital signs dataset when the one or more threshold values are crossed; and determining a magnitude of the anomaly. More preferably, the method further comprises determining a deviation and/or a frequency of the anomaly with reference to predicted values generated by a second prediction model trained based on an existing vital signs dataset and the magnitude of the one or more anomalies previously recorded. The deviation of the anomaly from the predicted value refers to the difference between the actual and predicted value of the anomaly and may be viewed as an anomalous anomaly. The frequency of the anomaly (or anomalies) refers to the number of anomalies in a time period, for example four anomalies in a 24 hour period. The deviation and frequency of the anomaly alone and in combination may be indicative of the person's health condition before symptoms may be observed especially for non-medically trained people which is often the case with caregivers taking care of patients at home.

Preferably, the magnitude of the anomaly is selected from the group consisting of: an absolute magnitude of the anomaly, a mean absolute error of the anomaly, a root mean square error of the anomaly, and combinations thereof.

Preferably, the method further comprises generating an alert when a spike in the magnitude of the anomaly is detected.

In an embodiment, the vital signs dataset comprises measured signal strength, and the one or more threshold values are determined by a signal strength anomaly model trained on past data of measured signal strength from the person's existing vital signs dataset.

In an embodiment, the vital signs dataset comprises at least one physiological signal selected from the group consisting of heart rate, heart rate variability, respiratory rate, temperature, blood pressure, oxygen saturation, and any combinations thereof.

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In an embodiment, the physiological signal is the heart rate, the vital signs dataset comprises heart rate data of the person and the one or more threshold values are determined by a heart rate anomaly detection model trained to predict the person's heart rate from the person's existing vital signs dataset.

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In an embodiment, the physiological signal is the heart rate variability, the vital signs dataset comprises heart rate variability data of the person and the one or more threshold values are determined by a heart rate variability anomaly detection model trained to predict the person's heart rate variability from the person's existing vital signs dataset.

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In an embodiment, the physiological signal is the respiratory rate, the vital signs dataset comprises respiratory rate data of the person and the one or more threshold values are determined by a heart rate anomaly detection model trained to predict the person's respiratory rate from the person's existing vital signs dataset.

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Preferably, the sensor data is received from a force sensor which is remotely located from the display of the vital signs dataset.

In a second aspect of the invention, there is provided a method of monitoring a patient, the method comprises reviewing the vital signs dataset displayed according to the first aspect; and determining if medical intervention is required.

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Preferably, the method further comprises administering treatment to the person based on the vital signs dataset.

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In a third aspect of the invention, there is provided a system comprising a bed; a sensor configured to measure a vital sign of a person in the bed; a transmission means; a database, wherein the sensor is configured to transmit sensor data to the database via the transmission means; a processor configured to generate a vital signs dataset from the sensor data; and a display device to display the vital signs dataset.

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Preferably, the system further comprises an alert module configured to compare the vital signs dataset against one or more threshold values, wherein the one or more threshold values comprises predicted values from a first prediction model trained on an existing vital signs dataset and a physiological range of the vital signs; and to generate an alert when
5 the one or more threshold values are crossed.

Preferably, the processor or alert module is configured to record an anomaly in the vital signs dataset when the one or more threshold values are crossed and to determine a magnitude of the anomaly. More preferably, the processor is configured to determine a
10 deviation and/or a frequency of the anomaly with reference to predicted values generated by a second prediction model trained based on an existing vital signs dataset and the magnitude of the one or more anomalies previously recorded.

Preferably, the magnitude of the anomaly is selected from the group consisting of: an
15 absolute magnitude of the anomaly, a mean absolute error of the anomaly, a root mean square error of the anomaly, and combinations thereof. More preferably, the alert module is configured to generate an alert when a spike in the magnitude of the anomaly is detected.

In an embodiment, the vital signs dataset comprises at least one of the following measured
20 signal strength or a physiological signal, wherein the physiological signal is selected from the group consisting of heart rate, heart rate variability, respiratory rate, temperature, blood pressure, oxygen saturation, and any combinations thereof.

Preferably, at least one of the following conditions is fulfilled:

25 the vital signs dataset comprises measured signal strength and the one or more threshold values are determined by a signal strength model trained on past data of measured signal strength from the person's existing vital signs dataset;

the vital signs dataset comprises heart rate data of the person and the one or more threshold values are determined by a heart rate anomaly detection model trained to predict
30 the person's heart rate from the person's existing vital signs dataset;

the physiological signal is the heart rate variability, the vital signs dataset comprises heart rate variability data of the person and the one or more threshold values are determined by a heart rate variability anomaly detection model trained to predict the person's heart rate variability from the person's existing vital signs dataset; and

35 the physiological signal is the respiratory rate, the vital signs dataset comprises respiratory rate data of the person and the one or more threshold values are determined by a heart

rate anomaly detection model trained to predict the person's respiratory rate from the person's existing vital signs dataset.

Preferably, the sensor is remotely located from the display device. Advantageously, the methods and systems may be remotely employed such that the patient and medical staff need not be present in the same premises and provides for greater efficiencies in the use of manpower and cost savings.

Preferably, the sensor is a force sensor. Advantageously, the use of a non-contact sensor is non-intrusive and does not provide discomfort to the patient being monitored in the bed. Further, as the force sensor does not require hardware to be attached to the patient, the use of the force sensor does not pose a safety risk to the patient.

In a fourth aspect of the invention, there is provided a non-transitory computer-readable medium comprising instructions, which when executed on a processor causes the processor to perform the method according to the first aspect.

Advantageously, the methods and systems described herein allow a patient to be monitored continuously and does not require active input by the patient or caregiver. In addition, embodiments which utilised a predictive model trained by machine learning allows for the generation of an alert when a threshold value is crossed and to further identify anomalies in a patient's physiological signal. In certain embodiments, the identified anomalies may be used to assist in medical staff in determining if medical attention is required. The output from the foundational models may be used alone or in combination in specialised models to generated additional predictions that may not be immediately apparent.

Detailed Description

In the Figures:

Fig. 1 shows a schematic of a patient monitoring system;

Fig. 2 shows a schematic of an embodiment;

Fig. 3 shows a bed sensor;

Figs. 4a and 4b show examples of a clinical study output;

Figs. 5a, 5b and 5c show examples of the data before and after data preparation;

Figs. 6a and 6b show the moving average of mean signal strength (MSS) across 24-hour periods;

Figs. 7a and 7b show the anomalies observed for a single patient's heart rate during and after a seizure event respectively;

Figs. 8a and 8b show the anomalies observed for a single patient's heart rate on a normal day and one day before demise respectively;

5 Fig. 9 shows the RMSE for heart rate per day over 30 days with clear spikes in RMSE about a week before death;

Fig. 10 shows spikes in a patient's heart rate beyond what is expected when the patient woke up during night sleep; and

10 Fig. 11a, 11b, 11c, 11d and 11e show the records of various recorded physiological signals of a patient during the course of an acute pneumonia episode. Fig. 11e splits the continuous horizontal chart into an upper part and a lower part. It may be noted the number of forecast errors in heart rate drops as the patient recovers from illness over the course of about 14 days.

15 In the following description, numerous specific details are set forth to provide a thorough understanding of various illustrative embodiments of the invention. It will be understood, however, to one skilled in the art, that embodiments of the invention may be practiced without some or all of these specific details. Embodiments described in the context of one of the methods or devices are analogously valid for the other methods or devices. Similarly,
20 embodiments described in the context of a method are analogously valid for a device, and vice versa.

The phrase "at least one of A and B" means it requires only A alone, B alone, or A and B, i.e. only one of A or B is required. As used herein, the articles "a", "an" and "the" as used
25 with regard to a feature or element include a reference to one or more of the features or elements. As used herein, the term "and/or" includes any and all combinations of one or more of the associated listed items. As used herein, the terms "first," "second," and "third," etc. are used merely as labels, and are not intended to impose numerical requirements on their objects.

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Where a combination is disclosed, each subcombination of the elements of that combination is also specifically disclosed and is within the scope of the invention. Conversely, where different elements or groups of elements are disclosed, combinations thereof are also disclosed. Where any element of an invention is disclosed as having a
35 plurality of alternatives, examples of that invention in which each alternative is excluded singly or in any combination with the other alternatives are also hereby disclosed; more

than one element of an invention can have such exclusions, and all combinations of elements having such exclusions are hereby disclosed.

Where a range of values is recited, it is to be understood that each intervening integer value, and each fraction thereof, between the recited upper and lower limits of that range is also specifically disclosed, along with each subrange between such values. The upper and lower limits of any range can independently be included in or excluded from the range, and each range where either, neither or both limits are included is also encompassed within the invention.

The embodiments described herein allows for (a) the detection of clinical deterioration in patients; and (b) quantify symptoms and correlate it to clinical outcomes.

Fig. 1 shows a schematic of a system 100 for monitoring a patient. The system has one or more monitoring sensors 101 each with a sensor application programming interface (API) that communicates with a data processing module 103. The data processing module 103 processes the data from the monitoring sensor/s 101 and sends the processed data to the visualisation module 104 and/or alert module 105 as described in greater detail below.

The visualisation module 104 and alert module 105 sends the processed data to a dashboard 106 (i.e. a user device) that allows a doctor or other medical personnel (patient care team) to view the data. Clinical data 107 may be further provided to supplement and correlate the collected data. The patient care team is thus able to use the collected data from the sensors to monitor and determine the patient's condition and allows for effective patient communications 108 (either in person or through teleconference) and administer care protocols 109 as required. The system 100 may be particularly useful for remote monitoring of patients at home or in a care facility where medical personnel may not be readily available.

The one or more patient monitoring sensors 101 may be contact or non-contact sensors and may be configured to measure at least one physiological signal of a person on a bed. The physiological signal measured may include heart rate, heart rate variability, respiratory rate, (body) temperature, blood pressure and oxygen saturation. The sensor 101 may measure the physiological signal directly or indirectly. A direct measurement sensor 101 may be one which measures the physiological signal directly, for example the heart rate or body temperature. An indirect measurement sensor 101 measures the physiological signal

indirectly, for example a force sensor or a motion sensor may be used to measure the movement of a person and convert the measurement to a physiological signal, for example heart rate and breathing rate. Sensors 101 which may measure the physiological signal indirectly may further have a processing unit to convert the actual sensor measurement to a physiological signal. For example, the movement sensor or force sensor may have a processing unit to convert the motion or force measured into a heart rate and/or respiratory rate of the person. Examples of monitoring sensors 101 may be any one selected from: a heart rate sensor, a respiratory rate sensor, a temperature sensor, a blood pressure sensor, an oxygen saturation sensor, a movement sensor (may also be called a motion sensor), and a location sensor. A movement sensor may use different type of sensing methods. Examples of different sensing means for a movement sensor include ultrasound, radar and infrared sensor. The sensors 101 are preferably configured to continuously collect data from the patient. The continuous data collection may be viewed as a passive data collection method by the sensor 101 where the sensor 101 is configured to measure the patient signs periodically (for example every second or every minute). The sensor 101 may also be configured to actively collect the data by a user either remotely or from the sensor 101 itself.

The data collected from the one or more sensors 101 may be sent to a data processing module 103 and may also be stored locally on the sensor device 101 itself. The transmission parameters of the sensor data may be configurable and period (for example every minute or every ten minutes) and largely depends on the type of data and bandwidth available. Further, data from the one or more sensors 101 may be combined and/or sent individually.

In an embodiment, there is a system 100 of care for patients at home to continuously monitor and provide clinician supporting data relevant for patient care. It includes the following components as seen in FIG. 1:

a) Deployment of continuous patient monitoring sensors (including sensor systems having a plurality of sensors) 101 in the home environment. The sensors may be capable of monitoring patient related data, such as heart rate, respiratory rate, temperature, blood pressure, oxygen saturation, movement, location, video, etc. are deployed on the patient as wearables, or through non-contact monitoring. The sensor 101 may measure the patient related data directly or indirectly. The sensor or sensor system 101 may continuously collect data and may be provided with a transmission means to transmit the collected data to a database 102 (i.e. a server), preferably continuously and a remote server (i.e. a server located at a different location from the patient and sensor). The term “continuous” as used

in this context refers to a prolonged and periodic time period and is not limited to a non-ending time period. For example, the sensor may measure and collect data every second or every minute. Similarly, the transmission of the data may be every second, every 30 seconds, or every minute and is typically determined by the size of the data packet, the transmission means and bandwidth available. The time period for the collection of the data by the sensor and transmission may be the same or different. Examples of the transmission means include wired and wireless mechanism like LAN, WLAN, WiFi, mobile devices, mobile gateway or other means.

b) Sensor data will be transmitted to the database 102 via the respective sensor's 101 communication protocols. Data processing is done to ensure compatibility of data structures from different sensor systems.

c) The data processing module 103 consumes data from the database 102 and processes the sensor data for:

i. Visualization module 104 - Sensor data is processed according to clinically relevant visualization charts.

ii. Alerts module 105 - Sensor data is processed and checked against thresholds for clinically relevant alerts. Alerts are triggered if thresholds are crossed and sent via SMS, email or other means to clinician user.

d) Clinician dashboard 106 integrates the various functions below and forms the basis for the clinician to organize care protocols. The clinical dashboard 106 may be viewed on a display device. It will enable the following functions:

(i) Visualize patient monitoring data;

(ii) Receive alert from alerts module 105 and allows clinician to handle alert;

(iii) Access clinical patient data 107 from electronic medical records and patient; and

(iv) Communications 108 with the care team e.g. emails, virtual chat or calls.

e) Clinical care support protocols 109 - Clinical care team monitors for alerts and responds according to care protocols relevant to situation.

The clinical patient data may include patient characteristics, age, sex disease etc. A database of patients with historical data and relevant events may also be included with updates when new events of interest occur.

Modules within the data processing module 103 that effect the data analysis may include the following functions: data quality check (offline, gaps, etc.), data conversion to align data from different device types, data pre-processing, data modelling, train and run one or more

foundational models and generate anomaly flags of each parameter and the time course of anomalies (area under curve), train and run one or more secondary models that combines result of foundational model for event prediction/ classification and interpretation of anomalies, A visualisation module 104 to generate graphs and charts of the parameters and an alert system 105 to generate alerts when one or more thresholds have been crossed.

Data conversion to convert data from different sensor types to common data format may be performed to allow the system to be device agnostic. Various methods including statistical modelling and deep learning may be performed on the raw data.

Following data collection from the one or more sensors 101 deployed in the patient's home, data is stored in a database 102 and processed by a module 103. The processed data may be displayed on a dashboard 106 (i.e. a display device) and alerts are generated based on an individual patient's thresholds and sent to the dashboard 106 if thresholds were crossed (for example too high or too low heart rate, or respiratory rate).

The continuous patient monitoring and communications support the clinician with an overview of the patient's clinical measurements and allows the clinician to provide appropriate treatment during ad-hoc or regular home care visits. This process of home care supplemented by technology has been implemented for elderly patients who have various acute and chronic conditions (e.g. pneumonia, cancer, stroke). Representations of the heart rate and breathing rate may be collected from a patient's continuous monitoring sensor/s 101 which is processed and displayed on the clinician dashboard 106. On being contacted by the terminally ill patient's family, a care team may be able to verify and interpret the patient's monitoring data as demise. A clinical response team may be subsequently dispatched to the patient's home for death certification as per clinical protocol.

In an embodiment, the sensor 101 is a force sensor 101 attached to the bed frame of a patient as shown in Fig. 2. Without being limited by theory, cardiac contractions cause pulsations in a person's blood vessels and body movements and is known as ballistocardiography (BCG). When the person is lying on a bed, the body movements are transmitted to the bed frame (the supporting structure of the patient). The force sensor 101 measures and collects data on the body movements. The force sensor 101 may be an accelerometer-based device that captures movements (forces). Based on the raw data, on-board processors in the force sensor 101 may compute the heart rate, respiratory rate, and heart rate variability (HRV). The signal strength parameter is a measure of the raw activity

(movement). Alternatively, the raw signal data may be collected and sent to the database 102 and processed remotely by the data processing module 103. Alternatively, part of the raw data is processed by the sensor 101 and further processing is done by the data processing module 103.

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The time interval between two heart beats may be abbreviated as B2B herein and is generally not constant across every beat within a time interval. HRV (heart rate variability) is a measure of the varying intervals between two heart beats of a person. For example, if there are 60 beats measured in a minute, the interval between beats 23 and 24 may be 1.6s and the interval between beats 38 and 39 may be 0.8s. But the average interval is 1s between all beats. HRV is thus a distinct measure than the heart rate and can be derived through various measures based on B2B.

From the raw signals measured by the sensor 101, the root mean square (RMS) of the raw signal may be determined to account for the large variation in spring constants due to the bed that result in different signal amplitude modulation and attenuation. The RMS value is reported as the measured signal strength of the sensor 101. The raw signals or the RMS of the raw signal may also be converted to a physiological signal of the patient such as a heart rate, heart rate variability, and respiratory rate of the patient by known methods. The signal strength, heart rate, heart rate variability, and respiratory rate of the patient may thus be derived from the raw signals by the sensor 101 itself (i.e. the sensor 101 has an onboard processor) or remotely.

The force sensor 101 (also known as the BCG bed sensor) may be mounted on the underside of the bed frame as shown in Fig. 3. The BCG bed sensor 101 allows for continuous monitoring while the patient is on the bed, and advantageously is non-contact, non-intrusive and not visible to the patient. The data from the BCG bed sensor 101 may be uploaded to a remote database 102 via Wi-Fi (or a LAN connection). The sensor 101 generally requires little to no maintenance after calibration of the sensor 101.

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The data processing module 103 generates a vital signs dataset from the sensor data received. The sensor data received may be of the raw signal measured by the sensor 101 and/or may be processed by the sensor to provide at least one of the following root mean square of the raw signal, measured signal strength, heart rate, heart rate variability, and respiratory rate. The vital signs dataset may be processed by the visualisation module 104 to be displayed on a dashboard 106 (i.e a display device) to allow the recorded vital signs

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dataset to be viewed by medical personnel. An alert module 105 may be configured to compare the vital signs dataset against one or more threshold values; and generate an alert when the one or more threshold values are crossed. The alert module 105 (or any other module like the data processing module 103) may record an anomaly in the vital signs dataset when the one or more threshold values are crossed; and to determine a root mean squared error of the anomaly compared to a predicted value generated by a prediction model trained based on an existing vital signs dataset. The alert module 105 may be further configured to generate an alert when a spike in the root mean squared error is detected. The existing vital signs dataset may contain the same type of sensor data as that received from the sensor presently and any anomaly recorded previously. The vital signs dataset may be made up of at least one of the following the raw signal data from the sensor; root mean square of the raw signal; measured signal strength; a physiological signal and any combinations thereof, Examples of a physiological signal that may be measured and recorded include respiratory rate, temperature, blood pressure, and oxygen saturation.

Fig. 4 shows an example of a clinical study output of a patient monitored by the systems 100 and methods described herein. Fig. 4a shows the data for the patient being managed for pain and confusion with Haloperidol and Pregabalin (brand name: Lyrica). A link between pain and restlessness is suggested by a spike in the heart rate in Fig. 4a. Fig. 4b shows the effect of changes in the treatment after Haloperidol was reduced to avoid side effects on sleep and Pregabalin was titrated up in response to continuing pain. A relative reduction in night-time activity was noted which is consistent with the patient's family report of the patient settling down to rest. Fig. 4b also shows a reduction in the heart rate after the change in the treatment provided.

In an embodiment, the data may be processed by one or more models to generate a prediction based on the data. In an embodiment, one or more foundational models may be used – a signal strength (SS) anomaly model (the signal strength is derived from the root mean square of the raw data from the sensor 101, for example the force sensor 101 described above), a heart rate (HR) anomaly detection model, a respiration rate (RR) anomaly detection model, and a heart rate variability (HRV) anomaly detection model. Any model technique applied to HR may also be applied to HRV, signal strength, RR, etc. The output from these foundational models may be used to feed into a more specialised model for specific use cases that require more complex feature engineering or integration of domain knowledge. Examples of specialised models include a death prediction model, a stress detection model and a sleep quality model. The use of a specific algorithm (or model)

with appropriate parameters may be used to detect anomalies and predicting death and/or clinical deterioration. It may be further extended to other uses like stress detection, confusion, sleep quality etc. of a patient.

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The data may be processed and output data of the signal strength (SS), heart rate (HR), respiration rate (RR) and heart rate variability (HRV) alone or in any combinations thereof.

10 Data from 30 patients were collected over a period of 10 months, and variables including heart rate (HR), respiratory rate (RR), measured signal strength (MSS), heart rate variability, time interval between heart beats (B2B), and event labels were used. The data was labelled for various events including seizure, demise, and others.

15 For each patient, the data was evaluated to determine if it was suitable for use. The evaluation criteria whether the data was fit for use includes at least 50 percent of on-bed readings per day (for example, $HR > 0$) for sufficiency and at least 10 continuous days of data for consistency. Of the 30 patients, data from 17 of the patients were found to be suitable for the modelling.

20 The data was subsequently prepared for modelling by the following:

Step 1: Removing entries with duplicate timestamps

Step 2: Removing *Heart Rate* = 0 (indicator for patient is off-bed)

Step 3: Removing very high *Measured Signal Strength* (MSS) (indicator for movement)

Step 4: Resample the time series data into 1 minute intervals

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Fig. 5a shows an example of how the raw data may look like. Fig. 5b shows the filtering for very high MSS and Fig. 5c shows the data after the data preparation steps outlined above.

30 In an embodiment, sleep analysis may be performed from the signal strength (SS) anomaly model. The SS anomaly model may include the following steps:

1. Several variables over time were modelled to identify patterns and get indications of sleep.
2. The change in Measured Signal Strength (MSS) was identified as a possible metric for sleep analysis.
- 35 3. Assumption: When a person sleeps, there is less movement - thus, MSS should be more stable

4. The median values of 10 days of MSS was used to calculate 60-min Rolling mean of change in MSS.
5. It was observed that a period of minimal change was observed at certain hours of night
- 5 6. The process was repeated for another patient and similar results were found.
7. Thus, the MSS may be used to predict sleeping patterns as the basis of the model and may be used to identify deviations from usual sleep patterns. Deviations in sleep patterns may be symptoms of other underlying medical conditions which may warrant further assessment. Thus, by identifying the deviations in sleep patterns early, it may be possible for the medical condition that cause the deviation to be treated at an early stage for a better treatment outcome.

Figs. 6a and 6b show the moving average of change in median MSS of two patients across a 24-hour period. It may be observed that there is a drop in the mean MSS around certain hours at night (grey area and marked by the arrow). This may be used for a sleep detection model. It may be seen that the thresholds are different for both patients and may be determined or set by machine learning.

Fig. 10 shows the heart rate of a patient. From Fig. 10 it may be observed that on each day there is a period when the heart rate decreases (a trough is observed), which is associated with periods of sleep. By comparing with the caregiver's record of the patient's activity, it was ascertained that on 7 August (08/07) the patient was asleep from 2140 (940 pm) to 0000 (12 am), briefly awakening before sleeping again till 0600 (6 am). On 8 August (8/8), the patient was asleep from 2145 (945 pm) to 0340 (340 am), briefly awakening before sleeping till 0630 (630 am). Fig. 10 shows that the periods of awakening may be determined by increases in the heart rate when patient is asleep. Periods of awakening may signal the patients is agitated or unwell. For example, a dementia or depressed patient may exhibit such disturbances in sleep patterns which improve after being medicated. By monitoring the sleep patterns and/or periods of awakening the doctor may track whether the prescribed drug dosages are adequate and to make changes as necessary.

In an embodiment, anomalies in the patient's vital signs may be detected. In a heart rate (HR) anomaly detection model. The model may contain the following steps:

1. The past 14 days (a preferred timeframe but any other number of days may be used) of Heart Rate data was used to make predictions for the next day.

2. Fbprophet was used for the analysis and prediction. The daily seasonality and weekly seasonality was accounted for as well. Other forecasting models may be used.
3. An anomaly is identified if the deviation of actual data from predicted data was beyond modelled thresholds, or if the actual data was outside physiologically feasible values (a heart rate of 40-110).
4. The magnitude of the anomaly was calculated to identify anomalous time periods. For example, the Root Mean Square Error (RMSE) & Mean Absolute Error (MAE) may be calculated to identify anomalous periods and to quantify the anomaly.

The above may be similarly applied to derive the heart rate variability (HRV) anomaly model and respiratory rate (RR) anomaly model. The outcome for the SS anomaly model, the HR anomaly model, the HRV anomaly model and the RR anomaly model are alerts that indicate time periods where HR, HRV, RR or SS are unusually high or low and warrant clinician review.

Figs. 7a and 7b show the anomalies (marked as circles) observed for a patient's heart rate on a seizure day and two days after a seizure event respectively. In Fig. 7a it may be seen that there is a large number of anomalies consistent with a seizure event. In Fig. 7b, it may be seen that the number of anomalies decreases significantly.

Figs. 8a and 8b show the anomalies observed for a patient on a normal day and a day before death respectively. It may be observed that on a normal day the patient only has a few anomalies in Fig. 8a whereas in Fig. 8b a large number of anomalies was observed in the patient's heart rate a day before the patient's demise. The stark difference between the anomalies detected may be used to alert the clinician and the patient's caregiver of a potential medical issue with the patient.

In an embodiment, the outputs from the four foundation models described – SS anomaly model, HR anomaly model, HRV anomaly model and RR anomaly model – may be used either alone or in combination in a specialised prediction model.

An example of a specialised prediction model may be a death prediction model which may be built with the following steps:

1. Identify anomalies in the Heart Rate before death using one or more of the foundational models (e.g. the heart rate anomaly detection model). Anomalies in the respiratory rate, heart rate variability, and signal strength may alternatively be used instead of the heart rate or in any combinations thereof.

2. The death prediction model was trained using 14 days of data to make predictions for the next day (and may further account for daily seasonality and weekly seasonality). In particular, the model may be trained on the number of anomalies within a time period and the duration of time in which the anomalies manifest, for example 30 minutes. Additional data on the patient may be included. For example, a non-exhaustive list may include the patient's age, sex and presence of diseases like cancer, dementia, stroke, Parkinson's, diabetes, hypertension and lipidmia.

3. The actual data is compared with the predicted data and the Root Mean Square Error (RMSE) for the day is calculated.

4. The deviation of the anomaly from the predicted anomalies (an anomalous anomaly) and the frequency of the anomalies may be determined. This allows medical staff to identify potential medical problem with the person, possibly even before any symptoms are observed or difficult to observe especially by non-medically trained caregivers.

The outcome or result of the death prediction model may be either binary (present/ absent) for a given day, or a probability of death occurring (e.g. 78% chance of patient dying the next day).

In an example of the death prediction model, the RMSE of the heart rate anomalies is recorded for a period of one month, leading up to the death date of two patients. The results indicate a sharp increase in RMSE about one week prior to death. Fig. 9 shows the RMSE of two patients over a period of 30 days and both patients show clear spikes in RMSE about a week before death. Thus, the spiking of the RMSE provides basis for the death prediction model or at least may provide the clinician with a cause of concern. Thus, the alert module 105 may be configured to generate an alert when a spike in the RMSE is detected.

Similarly, the outputs from the heart rate variability anomaly model and respiratory rate anomaly model may be fed into other specialised prediction models. Other specialised prediction models include stress detection model, sleep quality model, infection prediction model, hospitalisation prediction model, and increased nursing needs model.

Fig. 11a to Fig. 11d shows the physiological signals of a patient, in particular the heart rate, measured signal strength, heart rate variability and respiratory rate respectively. Fig. 11e shows the forecasted error of the patient based on the models described herein. The patient was seen on 11 July and treated with antibiotics for pneumonia. The patient improved clinically with no more fever and stable vital signs. The patient's condition may also be correlated with the physiological signals recorded. From Fig. 11a, it may be observed that the heart rate trend has stabilised to show the usual circadian variability. From Fig. 11e, it may be observed that there was reduction in the heart rate forecast errors following stabilisation of the patient's condition after treatment. In particular, it may be noted that the patient's heart rate stabilises over the course of 14 days, and there are no forecast errors after 14 days (25 July or 7/25). From Fig. 11d, it may be observed there was a reduction in respiratory rate following resolution of the patient's pneumonia. It may be noted that the respiratory rate drops as the patient recovers from illness over the course of about 14 days. The heart rate variability in Fig. 11c tallies with the patient's mood and agitation as recorded by the caregiver (for example the patient pulled out nasogastric tube (NGT) multiple times).

The systems and methods described herein allows for patients to be monitored remotely without requiring the physical presence of medical personnel, and may be of particular value for the care of patients in a residential setting, in particular geriatric, dementia, oncology, palliative, and long term care patients. Furthermore, the systems and methods allows medical personnel to triage patients remotely (through data analysis), and provide the necessary clinical response. Advantageously, this allows for patients to recover at home with family while receiving the same or similar standard of care as provided by medical personnel and also allows for the medical resources to be used for patients who require them the most.

The systems and methods described above may be implemented in many different ways in many different combinations of hardware, software, firmware, or any combination thereof. In one example, the systems and methods may be implemented with a computer having a processor and a memory communicably coupled thereto, where the memory stores instructions, which when executed by the processor, cause the processor to perform the aforementioned methods. The processor may include any type of circuit such as, but not limited to, a microprocessor, a microcontroller, a graphics processor, a digital signal processor, or another processor. The processor may also be implemented with discrete logic or components, or a combination of other types of analogue or digital circuitry,

combined on a single integrated circuit or distributed among multiple integrated circuits. All or part of the logic described above may be implemented as instructions for execution by the processor, controller, or other processing device and may be stored in a tangible or non-transitory machine-readable or computer-readable medium such as flash memory, random access memory (RAM) or read only memory (ROM), erasable programmable read only memory (EPROM) or other machine-readable medium such as a compact disc read only memory (CDROM), or magnetic or optical disk. A product, such as a computer program product, may include a storage medium and computer readable instructions stored on the medium, which when executed in an endpoint, computer system, or other device, cause the device to perform operations according to any of the description above. The memory can be implemented with one or more hard drives, and/or one or more drives that handle removable media, such as diskettes, compact disks (CDs), digital video disks (DVDs), flash memory keys, and other removable media.

The systems and methods can also include a display device, an audio output and a controller, such as a keyboard, mouse, trackball, game controller, microphone, voice-recognition device, or any other device that inputs information. The processing capability of the system may be distributed among multiple system components, such as among multiple processors and memories, optionally including multiple distributed processing systems. Parameters, databases, and other data structures may be separately stored and managed, may be incorporated into a single memory or database, may be logically and physically organized in many different ways, and may implemented in many ways, including data structures such as linked lists, hash tables, or implicit storage mechanisms. Programs may be parts (e.g., subroutines) of a single program, separate programs, distributed across several memories and processors, or implemented in many different ways, such as in a library, such as a shared library (e.g., a dynamic link library (DLL)). The DLL, for example, may store code that performs any of the system processing described above. The systems and methods can be implemented over a cloud.

Throughout this specification, plural instances may implement components, operations, or structures described as a single instance. Although individual operations of one or more methods are illustrated and described as separate operations, one or more of the individual operations may be performed concurrently, and nothing requires that the operations be performed in the order illustrated. Structures and functionality presented as separate components in example configurations may be implemented as a combined structure or component. Similarly, structures and functionality presented as a single component may be

implemented as separate components. These and other variations, modifications, additions, and improvements fall within the scope of the subject matter herein.

Certain embodiments are described herein as including logic or a number of components, modules, or mechanisms. Modules may constitute either software modules (e.g., code embodied on a machine-readable medium or in a transmission signal) or hardware modules. A “hardware module” is a tangible unit capable of performing certain operations and may be configured or arranged in a certain physical manner. In various example embodiments, one or more computer systems (e.g., a standalone computer system, a client computer system, or a server computer system) or one or more hardware modules of a computer system (e.g., a processor or a group of processors) may be configured by software (e.g., an application or application portion) as a hardware module that operates to perform certain operations as described herein.

In some embodiments, a hardware module may be implemented mechanically, electronically, or any suitable combination thereof. For example, a hardware module may include dedicated circuitry or logic that is permanently configured to perform certain operations. For example, a hardware module may be a special-purpose processor, such as a field programmable gate array (FPGA) or an ASIC. A hardware module may also include programmable logic or circuitry that is temporarily configured by software to perform certain operations. For example, a hardware module may include software encompassed within a general-purpose processor or other programmable processor. It will be appreciated that the decision to implement a hardware module mechanically, in dedicated and permanently configured circuitry, or in temporarily configured circuitry (e.g., configured by software) may be driven by cost and time considerations.

Accordingly, the phrase “hardware module” should be understood to encompass a tangible entity, be that an entity that is physically constructed, permanently configured (e.g., hardwired), or temporarily configured (e.g., programmed) to operate in a certain manner or to perform certain operations described herein. As used herein, “hardware-implemented module” refers to a hardware module. Considering embodiments in which hardware modules are temporarily configured (e.g., programmed), each of the hardware modules need not be configured or instantiated at any one instance in time. For example, where a hardware module comprises a general-purpose processor configured by software to become a special-purpose processor, the general-purpose processor may be configured as respectively different special-purpose processors (e.g., comprising different hardware

modules) at different times. Software may accordingly configure a processor, for example, to constitute a particular hardware module at one instance of time and to constitute a different hardware module at a different instance of time.

- 5 Hardware modules can provide information to, and receive information from, other hardware modules. Accordingly, the described hardware modules may be regarded as being communicatively coupled. Where multiple hardware modules exist contemporaneously, communications may be achieved through signal transmission (e.g., over appropriate circuits and buses) between or among two or more of the hardware
- 10 modules. In embodiments in which multiple hardware modules are configured or instantiated at different times, communications between such hardware modules may be achieved, for example, through the storage and retrieval of information in memory structures to which the multiple hardware modules have access. For example, one hardware module may perform an operation and store the output of that operation in a
- 15 memory device to which it is communicatively coupled. A further hardware module may then, at a later time, access the memory device to retrieve and process the stored output. Hardware modules may also initiate communications with input or output devices, and can operate on a resource (e.g., a collection of information).
- 20 The various operations of example methods described herein may be performed, at least partially, by one or more processors that are temporarily configured (e.g., by software) or permanently configured to perform the relevant operations. Whether temporarily or permanently configured, such processors may constitute processor-implemented modules that operate to perform one or more operations or functions described herein. As used
- 25 herein, “processor-implemented module” refers to a hardware module implemented using one or more processors.

Similarly, the methods described herein may be at least partially processor-implemented, a processor being an example of hardware. For example, at least some of the operations of

30 a method may be performed by one or more processors or processor-implemented modules. Moreover, the one or more processors may also operate to support performance of the relevant operations in a “cloud computing” environment or as a “software as a service” (SaaS). For example, at least some of the operations may be performed by a group of computers (as examples of machines including processors), with these operations being

35 accessible via a network (e.g., the Internet) and via one or more appropriate interfaces (e.g., an API).

The performance of certain of the operations may be distributed among the one or more processors, not only residing within a single machine, but deployed across a number of machines. In some example embodiments, the one or more processors or processor-implemented modules may be located in a single geographic location (e.g., within a home environment, an office environment, or a server farm). In other example embodiments, the one or more processors or processor-implemented modules may be distributed across a number of geographic locations.

Some portions of this specification are presented in terms of algorithms or symbolic representations of operations on data stored as bits or binary digital signals within a machine memory (e.g., a computer memory). These algorithms or symbolic representations are examples of techniques used by those of ordinary skill in the data processing arts to convey the substance of their work to others skilled in the art. As used herein, an “algorithm” is a self-consistent sequence of operations or similar processing leading to a desired result. In this context, algorithms and operations involve physical manipulation of physical quantities. Typically, but not necessarily, such quantities may take the form of electrical, magnetic, or optical signals capable of being stored, accessed, transferred, combined, compared, or otherwise manipulated by a machine. It is convenient at times, principally for reasons of common usage, to refer to such signals using words such as “data,” “content,” “bits,” “values,” “elements,” “symbols,” “characters,” “terms,” “numbers,” “numerals,” or the like. These words, however, are merely convenient labels and are to be associated with appropriate physical quantities.

Unless specifically stated otherwise, discussions herein using words such as “processing,” “computing,” “calculating,” “determining,” “presenting,” “displaying,” or the like may refer to actions or processes of a machine (e.g., a computer) that manipulates or transforms data represented as physical (e.g., electronic, magnetic, or optical) quantities within one or more memories (e.g., volatile memory, non-volatile memory, or any suitable combination thereof), registers, or other machine components that receive, store, transmit, or display information.

Certain examples of the present disclosure also relate to an apparatus for performing the operations herein. This apparatus may be constructed for the intended purposes, or it may comprise a general-purpose computer selectively activated or reconfigured by a computer program stored in the computer. Such a computer program may be stored in a computer readable storage medium, Such as, but not limited to, any type of disk including floppy disks,

optical disks, CD-ROMs, and magnetic-optical disks, read-only memories (ROMs), random access memories (RAMs), EPROMs, EEPROMs, magnetic or optical cards, or any type of media suitable for storing electronic instructions.

CLAIMS

1. A computer-implemented method of monitoring a person's health condition, the method comprising
 - (a) receiving sensor data of a person in a bed;
 - (b) generating a vital signs dataset from the sensor data; and
 - (c) displaying the vital signs dataset.
2. The method according to claim 1 further comprising comparing the vital signs dataset against one or more threshold values, wherein the one or more threshold values comprises predicted values from a first prediction model trained on an existing vital signs dataset and a physiologically feasible range of the vital signs; and generating an alert when the one or more threshold values are crossed.
3. The method according to claim 2 further comprising recording an anomaly in the vital signs dataset when the one or more threshold values are crossed; and determining a magnitude of the anomaly.
4. The method according to claim 3 further comprising determining a deviation and/or a frequency of the anomaly with reference to predicted values generated by a second prediction model trained based on an existing vital signs dataset and the magnitude of the one or more anomalies previously recorded.
5. The method according to any one of claims 2 to 4 wherein the magnitude of the anomaly is selected from the group consisting of: an absolute magnitude of the anomaly, a mean absolute error of the anomaly, a root mean square error of the anomaly, and combinations thereof.
6. The method according to any one of claims 4 to 5 further comprising generating an alert when a spike in the magnitude of the anomaly is detected.
7. The method according to any one of claims 1 to 6 wherein the vital signs dataset comprises measured signal strength, and the one or more threshold values are determined by a signal strength anomaly model trained on past data of measured signal strength from the person's existing vital signs dataset.

8. The method according to any one of claims 1 to 7 wherein the vital signs dataset comprises at least one physiological signal selected from the group consisting of heart rate, heart rate variability, respiratory rate, temperature, blood pressure, oxygen saturation, and any combinations thereof.
- 5
9. The method according to claim 8 wherein the physiological signal is the heart rate, the vital signs dataset comprises heart rate data of the person and the one or more threshold values are determined by a heart rate anomaly detection model trained to predict the person's heart rate from the person's existing vital signs dataset.
- 10
10. The method according to any one of claims 8 to 9 wherein the physiological signal is the heart rate variability, the vital signs dataset comprises heart rate variability data of the person and the one or more threshold values are determined by a heart rate variability anomaly detection model trained to predict the person's heart rate variability from the person's existing vital signs dataset.
- 15
11. The method according to any one of claims 8 to 10 wherein the physiological signal is the respiratory rate, the vital signs dataset comprises respiratory rate data of the person and the one or more threshold values are determined by a heart rate anomaly detection model trained to predict the person's respiratory rate from the person's existing vital signs dataset.
- 20
12. The method according to any one of claims 1 to 11 wherein the sensor data is received from a force sensor which is remotely located from the display of the vital signs dataset.
- 25
13. A method of monitoring a patient, the method comprises reviewing the vital signs dataset displayed according to any one of claims 1 to 12; and determining if medical intervention is required.
- 30
14. The method according to claim 13 further comprising administering treatment to the person based on the vital signs dataset.
- 35
15. A system comprising a bed; a sensor configured to measure a vital sign of a person in the bed; a transmission means; a database, wherein the sensor is configured to transmit sensor data to the database via the transmission means; a processor

configured to generate a vital signs dataset from the sensor data; and a display device to display the vital signs dataset.

- 5 16. The system according to claim 15 further comprising an alert module configured to compare the vital signs dataset against one or more threshold values, wherein the one or more threshold values comprises predicted values from a first prediction model trained on an existing vital signs dataset and a physiological range of the vital signs; and to generate an alert when the one or more threshold values are crossed.
- 10 17. The system according to claim 16 wherein the processor or alert module is configured to record an anomaly in the vital signs dataset when the one or more threshold values are crossed and to determine a magnitude of the anomaly.
- 15 18. The system according to claim 17 wherein the processor is configured to determine a deviation and/or a frequency of the anomaly with reference to predicted values generated by a second prediction model trained based on an existing vital signs dataset and the magnitude of the one or more anomalies previously recorded.
- 20 19. The system according to any one of claims 16 to 18 wherein the magnitude of the anomaly is selected from the group consisting of: an absolute magnitude of the anomaly, a mean absolute error of the anomaly, a root mean square error of the anomaly, and combinations thereof.
- 25 20. The system according to claim 19 wherein the alert module is configured to generate an alert when a spike in the magnitude of the anomaly is detected.
- 30 21. The system according to any one of claims 15 to 20 wherein the vital signs dataset comprises at least one of the following measured signal strength or a physiological signal, wherein the physiological signal is selected from the group consisting of heart rate, heart rate variability, respiratory rate, temperature, blood pressure, oxygen saturation, and any combinations thereof.
22. The system according to claim 21 wherein at least one of the following conditions is fulfilled:

- (a) the vital signs dataset comprises measured signal strength and the one or more threshold values are determined by a signal strength model trained on past data of measured signal strength from the person's existing vital signs dataset;
- 5 (b) the vital signs dataset comprises heart rate data of the person and the one or more threshold values are determined by a heart rate anomaly detection model trained to predict the person's heart rate from the person's existing vital signs dataset;
- 10 (c) the physiological signal is the heart rate variability, the vital signs dataset comprises heart rate variability data of the person and the one or more threshold values are determined by a heart rate variability anomaly detection model trained to predict the person's heart rate variability from the person's existing vital signs dataset; and
- 15 (d) the physiological signal is the respiratory rate, the vital signs dataset comprises respiratory rate data of the person and the one or more threshold values are determined by a heart rate anomaly detection model trained to predict the person's respiratory rate from the person's existing vital signs dataset.
- 20 23. The system according to any one of claims 15 to 22 wherein the sensor is remotely located from the display device.
24. The system according to any one of claims 15 to 23 wherein the sensor is a force sensor.
- 25 25. A non-transitory computer-readable medium comprising instructions, which when executed on a processor causes the processor to perform the method according to any one of claims 1 to 12.